Machine Learning-based Room Recognition

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***Abstract*—Nowadays smartphones can collect huge amounts of data from their surroundings with the help of embedded sensors. The combination of these sensor values, such as Wi-Fi Received Signal Strengths and magnetic field measurements, is assumed to be unique in some locations, which can be used to accurately predict smartphones' indoor locations. In this work, we apply machine learning methods to derive the correlation between smartphones' locations and the received Wi-Fi signal strength and sensor values, and we have developed an Android application that is able to distinguish between rooms. Our real-world experiment results show that the Voting ensemble predictor outperforms individual machine learning algorithms and it achieves an indoor room recognition accuracy of 94% in office-like environments. This work provides a coarse-grained indoor room recognition, which can be envisioned as a basis for accurate indoor positioning.**

I. Introduction

Indoor environments provide many different ubiquitous radio signals, such as Wi-Fi, Bluetooth, magnetic field, sound, light, etc. The earth magnetic field (MF) has distortions over space due to the presence of ferromagnetic materials. These MF distortion patterns can be also used to identify indoor locations. Thereby, MF and Wi-Fi observations can be used as radio fingerprints to detect unique locations in indoor environments.

In this work, we propose to use supervised Machine Learning (ML) methods to process this large amount of collected data. By training a classifier (supervised learning algorithm such as K-Nearest-Neighbor) on the collected labeled data, rules can be extracted. Feeding in the actual live data (RSS values, magnetic field values, illuminance level, etc.) of a moving user, the trained classifier can then predict the user's location in a coarse-grained level. We propose to apply machine learning methods, both individual predictors and ensemble predictors, to solve this task due to the large amount of features that are available in indoor environments, such as Wi-Fi RSS values, magnetic field values and other sensor measurements. We expect that ensemble predictors can outperform the individual machine learning algorithms to discover patterns in the data which can then be used to differentiate between different rooms in office-like indoor environments.

II. Machine Learning-based Room Recognition

A. Algorithms

In this work, we use the following algorithms to perform the room recognition.

1) Naive Bayes (NB): classifiers are a family of simple probabilistic classifiers based on applying Bayes' theorem with strong (naive) independence assumptions between the features.

2) K-Nearest Neighbors (KNN): is a non-parametric method used for classification and regression. In both cases, the input consists of the k closest training examples in the feature space.

3) Support Vector Machine (SVM): is a supervised learning model with associated learning algorithms, which builds a model that assigns new data measurements to one category or the other, making it a non-probabilistic binary linear classifier.

4) Multilayer Perceptron (MLP): is a class of feed-forward artificial neural network. An MLP consists of at least three layers of nodes, and each node is a neuron that uses a nonlinear activation function.

5) Voting: is one of the simplest ensemble predictors, which combines the predictions from multiple individual predictors. A Voting classifier can then be used to wrap the models and average the predictions of the sub-models when asked to make predictions for new data.

B. Features

In a machine learning-based classification task, the attributes of the classes are denoted as features. Each feature is describing an aspect of the classes. In our case features are our measurements, for instance a Wi-Fi RSS value. To deliver good machine learning prediction accuracy it is very important to select the right features and to also modify certain features or even create new features out of existing features.

1) Wi-Fi RSS: Values provide the core data as they contribute the most to the performance of the ML methods. The smartphone scans the surrounding Wi-Fi access points, obtains and registers the RSS values of each access point. Wi-Fi RSS values depend on the distance between the smartphone and the Wi-Fi access points.It has a normal value of -20 dBm to -90 dBm.

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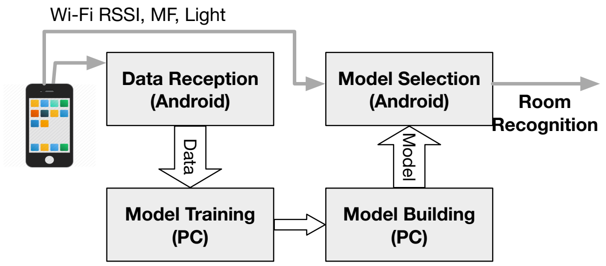

Fig. 1: The architecture of the implemented Android app.

2) Magnetic Field (MF): The device's sensors measure the magnetic field in the device's coordinate system. As the user walks around, the orientation of the device may change all the time. Therefore, we have to collect all possible values from every orientation in every point in the training phase. This would result in a huge amount of data and the training performance would be inaccurate.

3) Light: Light sensors might also be helpful to identify rooms. For instance, a room facing a window will clearly be brighter than one surrounded by walls only. As shown in Section IV, this does improve the prediction accuracy. However, these assumptions are not stable, as the illuminance level might change over time. Therefore, it is better to work with light differences instead of absolute values.

III. Experiments and Results

Figure 1 shows the system model. We made experiments in an office area of $288m^2$. We have collected 14569 data points in total, and the data collection takes around 50 minutes. With the collected data, we built models with different fingerprints data: the first one using only Wi-Fi RSSI data, the second one using Wi-Fi RSS together with MF readings, and the third one with Wi-Fi RSS, MF readings, and illuminance level readings. In our experiments, we do not need to know the locations of the Wi-Fi APs, while only the fingerprints of Wi-Fi RSSI, MF readings, and illuminance level readings are needed. We define the 9 separated areas as 9 rooms. During the online testing phase, a person holding the smartphone walks through the 9 rooms and his location is recognized in real-time based on the collected data.

A nested cross validation technique is used to optimize hyperparameters of the machine learning algorithms. The inner cross validation is to select the model with optimized hyperparameters, whereas outer cross validation is to obtain an estimation of the generalization error. For KNN, we optimized the global blend percentage ratio hyperparameter, kernel type function for SVM, number of hidden layers and neurons per layer for MLP. Based on the parameter optimization process, we established the optimal hyperparameter values for the classifiers as follows: blend percent ratio of 30% for KNN, single order polynomial kernel, $c = 1$, $\gamma = 0.0$ for SVM, and single hidden layer with 10 neurons for MLP.

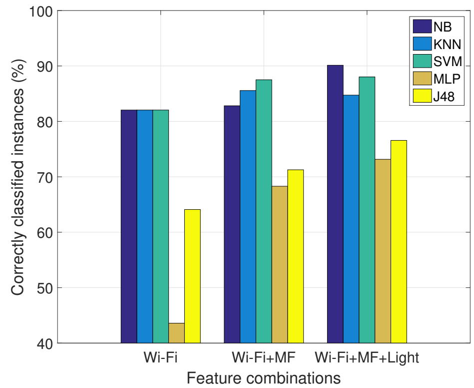

Fig. 2: Room recognition results with different features.

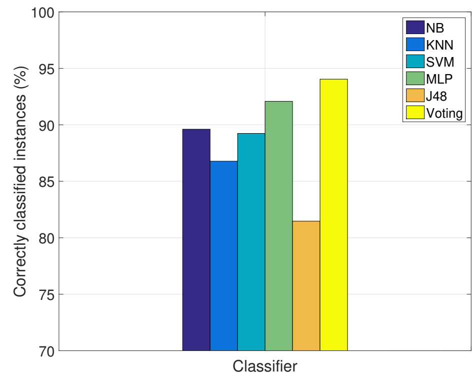

Fig. 3: Room recognition results with optimized hyperparameters.

Figure 2 shows the performance evaluation of the selected classifiers obtained with different feature combinations. The best performance is reached by the Naive Bayes classifier, which achieves 90.13% of instances correctly classified if the fingerprint is composed by Wi-Fi RSS, MF readings, and illuminance levels. By using Wi-Fi RSS, MF readings, and illuminance levels in the room landmark recognition, the accuracy is improved in all tested classifiers. Figure 3 shows the performance of the selected classifiers with the hyperparameters optimized and using Wi-Fi RSS, MF and illuminance levels. Compared to Figure 2, all the classifiers have improved performance, and MLP even reaches an accuracy of 92.08%. We also include the results of Voting, which combines the prediction results of MLP, Naive Bayes, KNN, and SVM using majority vote. It shows that Voting can reach an accuracy of 94.04%.

IV. Conclusions

This work applies machine learning methods for indoor room recognition. Results show that Voting achieves the best room recognition accuracy of 94%.

Disclaimers

The full version of this paper has been accepted for publication in the 16th International Conference on Wired/Wireless Internet Communications (IFIP WWIC), and can be found at http://dx.doi.org/10.7892/boris.116245.

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